Available online at www.sciencedirect.com

ScienceDirect

Procedia Computer Science 28 (2014) 120 – 129

Procedia Computer Science

Conference on Systems Engineering Research (CSER 2014)

Eds.: Azad M. Madni, University of Southern California; Barry Boehm, University of Southern California; Michael Sievers, Jet Propulsion Laboratory; Marilee Wheaton, The Aerospace Corporation
Redondo Beach, CA, March 21-22, 2014

A Framework for Optimizing the Use of Systems Engineering on Proposals

Clement Smartt[a]*, Susan Ferreira[a], Jay Rosenberger[b], H.W. Corley[b]

[a]*The University of Texas at Arlington, Systems Engineering Research Center, Arlington, Texas 76019, USA*
[b]*The University of Texas at Arlington, Center on Stochastic Modeling, Optimization, & Statistics, Arlington, Texas 76019, USA*

Abstract

Organizations that execute contracts must capture them to survive. Systems engineering often leads the technical activities in the proposal process. Therefore, it is important that systems engineering be applied effectively on proposals. This paper introduces a framework for developing models to find an optimal use of systems engineering on proposals. Optimization models developed using the framework can maximize an objective function of interest such as the probability of contract award on a proposal by leveraging data from previous proposal efforts. These optimization models provide recommendations as to how much budget to invest in systems engineering on proposals and how to allocate that budget across various systems engineering activities and to contributors with various skill levels. This paper describes the framework and provides guidance for how to develop an optimization model using the framework that is customized for a particular proposal effort of interest. The validation of the framework is also described.

Selection and peer-review under responsibility of the University of Southern California.

Keywords: *systems engineering; optimization; framework; proposal*

* Corresponding author. Tel.: (817) 272-3092; fax: (817) 272-3408.
E-mail address: clement.smartt@mavs.uta.edu

1877-0509 © 2014 The Authors. Published by Elsevier B.V.
Selection and peer-review under responsibility of the University of Southern California.
doi:10.1016/j.procs.2014.03.016

1. Introduction

Organizations that execute contracts must capture them to survive. Proposals are generally how organizations capture contracts. When complex systems are being engineered, systems engineering often leads the technical activities on proposals. Systems engineering can be used to help align the technical competencies of the organization with market opportunities and to help define the solution that will be offered in a proposal[1]. A relatively new area of systems engineering research is the use of systems engineering on proposals[2]. Little research has been done in this area, and a number of challenges and opportunities have been defined related to the use of systems engineering on proposals[3]. One of the identified opportunities that is especially important is optimizing the use of systems engineering on proposals. A recently completed doctoral dissertation[4] focused on an optimal use of systems engineering on proposals. This conference paper is a summary of a portion of the doctoral research pertaining to a framework to help decision makers find an optimal use of systems engineering on proposals. For a more detailed description of the framework or any aspects of the framework, the reader should consult the dissertation.

2. Optimizing the Use of Systems Engineering on Proposals

Optimization helps decision makers responsible for proposal success make the best decisions that they can given their situation. Optimization is achieved by minimizing or maximizing a function, usually subject to some equality or inequality constraints[5]. This function is called an objective function and mathematically expresses the objective that the decision maker seeks to optimize. Constraints define the set of alternatives that are truly options. A subset of the independent variables in the objective function is called decision variables. Decision variables are defined as "a quantity that a decision maker controls"[6]. This section discusses the objective function, the constraints, and the decision variables. Then a framework for optimizing the use of systems engineering on proposals is introduced.

2.1. The Objective Function

For proposal management, there are a number of potential objectives that can be optimized[1]. These include proposal project specific objectives such as maximizing the value of real options, maximizing the net present value of a proposal opportunity, maximizing the probability of a contract award, and minimizing the cost of preparing a proposal. There are also more broadly focused objectives such as using proposals to maximize the capital position of an organization, minimize the idle rate of staff, or maximize the likelihood of repeat business.

For the framework defined in this paper, there are many potential objectives that can be used, but maximizing the probability of a contract award is the objective chosen to illustrate the framework. This objective is especially relevant because a primary purpose of proposal management is to be awarded a contract[1]. Stakeholders of proposal management, including project managers, proposal managers, lead engineers, lead systems engineers, functional managers, and individual contributors may benefit from maximizing the probability of contract awards for reasons discussed in Smartt and Ferreira[1]. Due to the importance of this objective, there are many examples of papers that address how to maximize the probability of winning bids[7,8,9,10]. Maximizing the probability of a contract award, however, is just a starting point for this type of analysis. Section 6 will discuss potential future work related to other important objectives.

2.2. The Constraints

The framework presented here is sufficiently flexible to allow a number of different types of constraints based upon the situation. In general, the constraints for optimizing the use of systems engineering on proposals pertain primarily to limitations on available time or resources. The discussion in this paper focuses on resource limitations and leaves models with a temporal component (e.g., time constraints) for future work. In most cases, organizations submitting proposals to engineer a system must pay for some or all of the proposal costs using the organization's resources. In many cases, decision makers have been assigned an existing budget that must be adhered to. In other cases, there is some flexibility about the budget. Often in these more flexible cases, however, rationale has to be provided to senior management as to why a certain amount of budget is needed. The budget may have to cover a number of expenses,

including items such as travel, overhead costs (e.g., equipment and facilities) or the costs of materials for generating the proposal package. However, when complex systems are involved, a leading cost factor is the labor costs of the time of employees who are contributing to the definition of the system being proposed. In many organizations, labor costs are related to the take home pay of the employees. More senior employees have higher salaries, and therefore their labor costs more per hour. Less senior employees have lower salaries, and therefore their labor costs less per hour. The total costs of labor (hours of employee time multiplied by the hourly labor rate by employee) plus the other proposal costs must be less than or equal to the budget.

Besides budget, another potential constraint is the availability of personnel. In some cases, an individual with certain specialized skills at particular levels of expertise may not be available to work on a proposal of interest or may be available, but have a limited number of hours that can be assigned to the proposal. If an optimization model recommends using an individual who is unavailable or using more labor hours than the individual has available, then the output of the optimization model is not feasible and is of limited use to the decision maker. In medium or large organizations, there are often multiple individuals who have specialized skills at a particular level. It may be the case that one of the individuals is not available but another one is available. Therefore, it may make sense to specify the availability of groups of individuals with similar skills and skill levels versus the availability of actual individuals. In many cases, constraints are somewhat flexible and models developed from a framework such as this can be used to better understand the relationships between the constraint values and the objective function value. This insight may help justify requesting an increased budget or why an expert at a particular skill should be added to the proposal team.

2.3. The Decision Variables

The decision variables may vary depending upon what aspects of the problem are under the control of the decision maker and what variables are related to the objective of interest. Optimizing the use of systems engineering on proposals requires selecting decision variables. To select possible decision variables, Smartt[4] identified a number of systems engineering related factors that are statistically positively correlated with the probability of a contract award. These include the level of satisfaction of customers on previous or ongoing contracts, the relative (to contract size) number of systems engineering labor hours devoted to key systems engineering activities, and the relative (to contract size) number of face-to-face contacts between the supplier and customer during the proposal process.

Of the various types of factors found to be significant, one type of factor that is especially of interest is the number of systems engineering labor hours devoted to key systems engineering activities in the proposal process. Unlike some other factors, the relative systems engineering labor can be controlled at the time of the proposal. For example, individuals responsible for making resource allocation decisions on proposals can specify how much budget is to be invested in the proposal effort and also identify how that budget will be allocated to various systems engineering activities and employees with various skill levels. In contrast, there are other important factors, such as the level of customer satisfaction on previous or ongoing contract work, that are already determined prior to the proposal activities.

Systems engineering labor on proposals has a cost. It would be helpful to determine an optimal level of investment in systems engineering labor on a proposal. A complementary goal is for any budget level, to invest that budget so that the probability of a contract award is maximized. It is desirable to allow decision makers the flexibility to define the decision variables as they please.

2.4. An Optimization Framework

This paper describes a framework called the Systems Engineering Proposal Optimization Modeling Framework (SEPOMF). A framework is defined as "a basic conceptual structure (as of ideas)"[11]. The SEPOMF allows for various objective functions, constraints and decision variables to be used. The goal is to allow an organization that is supplying complex systems to maximize an objective of interest for a future proposal effort by leveraging data from past proposal efforts.

The SEPOMF helps decision makers develop and solve optimization problems to answer important questions. This paper explores using the SEPOMF with a particular type of objective function, maximizing the probability of contract award, to determine how much budget to invest on certain systems engineering activities and what mix of skill levels of employees is best to perform those activities. This paper illustrates the SEPOMF by discussing inputs and outputs

and presents the formal mathematical programming definition of the optimization problem at the core of the example. This paper also discusses how to apply the framework to a particular proposal effort using historical data from previous proposal efforts and discusses the validation process for the framework.

3. Illustrating the SEPOMF Using an Example DSS

The SEPOMF allows analysts to develop decision support systems to optimize an objective of interest related to the use of systems engineering on proposals. In order to define the SEPOMF, it is necessary to have a clear vision of what a decision support system (DSS) generated using the SEPOMF should do. A DSS helps people make decisions[12]. A DSS is especially helpful for problems related to decision making that involve both known and unknown components[13]. A use case analysis[14] was conducted to define exactly what an example DSS developed using the SEPOMF should do, who will use the DSS, and inputs and outputs of the DSS. The example DSS derived from the use case analysis is defined in this paper, but has not yet been fully developed because not enough data is available to derive the parameters values in an objective function that is sufficiently complex to yield meaningful results.

The inputs to the example SEPOMF DSS include factors related to the contract, the systems engineering organization (including the labor rates and availability of professionals with particular systems engineering skill sets at particular skill levels), the competition, the customer relationship, the proposal effort, and the budget. The outputs include a curve that expresses the values of the objective function vs. the budget spent. For the example DSS, the curve is probability of contract award vs. budget spent. The example DSS outputs the number of labor hours to invest in certain systems engineering activities and particular skill levels for those activities.

At the core of each SEPOMF DSS is an optimization problem. The optimization problem in the example SEPOMF DSS is defined below.

Example SEPOMF DSS objective function:

$$z(B) = \max(\hat{P}(x))$$

Example SEPOMF DSS constraints:

$$x_{ij} \le u_{ij} \text{ for all } i \text{ and } j \tag{1}$$

$$x_{ij} \ge 0 \quad \text{for all } i \text{ and } j \tag{2}$$

$$\sum_i \sum_j t_{ij} x_{ij} \le B \tag{3}$$

In this formulation, the vector x is the set of decision variables such that x_{ij} is the number of systems engineering labor hours for contributors of skill level j on activity i, u_{ij} is the maximum number of systems engineering labor hours that are available for skill level j on activity i, t_{ij} is the hourly labor rate for contributors (including overhead loading) at skill level j on activity i, and B is the budget available for systems engineering labor. Significant care needs to be applied determining B based upon the total resources available for the proposal. Cost factors potentially not included in the overhead loading such as capital expenditures, costs for travel, and costs for specialized equipment or supplies also need to be considered when determining B.

The objective function $\hat{P}$ is a function that estimates the probability of a contract award. In the example DSS, $\hat{P}$ is developed through regression analysis (e.g., logistic regression analysis) using historical proposal data from the organization. The SEPOMF is sufficiently flexible that organizations can customize the set of decision variables to use the data that they already have collected. The objective function can also be a function of variables other than the decision variables. Some of the other variables may not be under the immediate control of the decision makers, such as the level of customer satisfaction on existing contract work. Nonetheless, these factors may impact the optimal strategy for investing in systems engineering labor for a particular proposal opportunity. A more extensive discussion

of both the objective function and constraints is offered in the next section.

4. Process for Applying the SEPOMF

The SEPOMF provides guidance for decision makers through the complete optimization modeling process, including the following steps: (1) determine what historical data is usable, (2) identify decision variables, (3) derive and select an objective function, (4) determine constraints, (5) define and solve an optimization problem, and (6) interpret and act on the results. Figure 1 provides an overview of the major steps recommended when applying the SEPOMF. The following subsections will discuss each of these major steps.

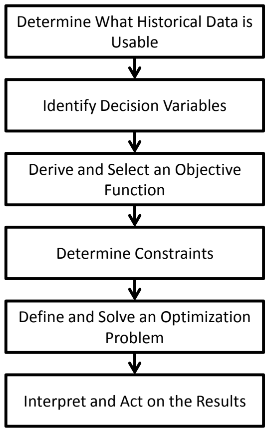

Fig. 1. Process for applying the SEPOMF.

4.1. Determine What Historical Data is Usable

One of the greatest challenges in developing a DSS using the SEPOMF is determining what set of historical data should be used in the regression analysis to develop the objective function. Using historical data that is different in some fundamental way than the current proposal should be avoided. Of course, the challenge is determining what constitutes "fundamentally different". A set of questions help decision makers determine the appropriateness of using historical data. For each historical proposal effort considered, these questions pertain to (1) whether the processes are basically the same that were used on the historical proposal as they are now, (2) whether the historical proposal was for the same general type of effort (e.g., development of a system, maintenance of a system) as the current proposal, and (3) whether the historical proposal was for the same type of customer.

Generally speaking, affirmative answers to these questions are necessary but not sufficient to justify using a historical proposal effort when developing a DSS. It is possible that a recent proposal for a similar type of effort for a similar customer may not be appropriate for some other reason. For example, if the proposal of interest is for a large contract and is expected to employ a whole team of systems engineers, it may not be wise to include a proposal effort for a very small contract that required a very limited systems engineering effort all performed by one person. While the SEPOMF provides a mechanism to normalize proposal efforts by contract size, how systems engineering is used on very small proposals may be fundamentally different from how systems engineering is used on very large proposals.

4.2. Identify Decision Variables

Analysts may select any decision variables that are meaningful in the context of their proposal efforts or that correspond with how the available historical data is organized. In general, the following should be satisfied by the set of decision variables selected for a SEPOMF model:

1. All decision variables should relate to well-defined items in the problem space.

2. All decision variables should be mutually exclusive. For example, there should be no task or effort that could count toward more than one of the decision variables.
3. The decision variables should be organized in a way that is consistent with how the historical data that is used to calibrate the regression model is organized. The various categories that were used to record the historical data should be considered as a possible set of decision variables.

4.3. Derive and Select an Objective Function

The objective function may assume different forms depending upon what objective is being pursued. In the example SEPOMF DSS, the objective function form is a multivariate logistic regression equation. This form is suitable because the objective function expresses a probability of an event (e.g., a contract award), and each historical data point has a binary outcome. In other words, each historical data point either experienced an event (e.g., a contract award) or did not experience an event (e.g., no contract award). Logistic regression equations have been used to model a number of relationships with similar structure such as the probability that a family will buy a new car as a function of income[15] and the probability that an organization will submit a bid for a particular bid opportunity as a function of a number of factors[16]. A number of techniques are described in texts on regression analysis[17,18] for selecting the best regression model given a set of data. These include forward selection, stepwise selection, backward deletion, and best subsets. These approaches are applicable to logistic regression as well as linear regression. Using these techniques, a number of potentially useful models can be developed that express the probability of contract award as a function of the decision variables and other pertinent factors.

A number of metrics exist that can be used to compare various regression models. These metrics include indices also used in linear regression analysis that reward high explanatory power and penalize excessive terms such as Akaike Information Criterion (AIC) and Schwartz Criterion (SC)[17]. Low AIC and SC values are desirable. Another very important metric that is more specific to multivariate logistic regression models is events per variable (EPV)[19,20]. Maintaining an adequate EPV essentially constrains the number of parameters (and hence number of factors) that can be in a logistic regression model based upon the historical data available.

4.4. Determine Constraints

The constraints described in Section 3 are determined by the available resources, and must be specified explicitly in order for the optimization model to produce recommendations that are feasible. For the example DSS, these constraints includes both the overall budget (Constraint #3) for the systems engineering activities on the proposal effort as well as the actual availability of individuals in a category corresponding to a decision variable (Constraint #1). For any category corresponding to a decision variable, the number of labor hours must be less than or equal to the number of available labor hours for individuals in that category. Also, the total labor costs (number of labor hours times cost per labor hour) cannot exceed the budget. Another more subtle constraint is that the number of labor hours for each decision variable must be non-negative (Constraint #2). If this non-negative constraint is not explicitly specified, the model may recommend a negative number of labor hours be devoted to certain individuals with particular skill levels. Labor hours, of course, cannot be negative.

4.5. Define and Solve an Optimization Problem

Once the objective function and constraints are identified, the optimization problem must be formally coded and solved. Given the potential mathematical complexity of the objective function and constraints, it may be advisable to use a specialized software package for solving the optimization problem that has a global optimization capability. The type of optimization algorithm used will depend on the structure of the objective function and nature of the constraints. For example, if the objective function is a continuous, nonlinear function, then one would use nonlinear programming to solve the problem.

4.6. Interpret and Act on the Results

After an optimal solution has been found, it is essential to translate the model results into variables that are meaningful to decision makers. For instance, the example SEPOMF DSS will find an optimal ratio of the number of systems engineering labor hours to a metric quantifying the estimated contract size. Examples of potential metrics that could be used to quantify contract size include the number of labor hours projected to be worked on the contract, the number of expected requirements, and the estimated total ownership cost. Careful thought should be devoted to selecting a size metric that seems appropriate to correspond to the level of systems engineering effort that is necessary to support defining the proposed offering. It is important to use these ratios and convert the model results into units of measurement that are meaningful to decision makers such as the number of labor hours. Once this translation is done, estimates from the SEPOMF DSS should be compared to estimates derived from other means (e.g., bottoms up estimates, expert estimates) to verify that the SEPOMF DSS results make sense.

When using a SEPOMF DSS to make decisions, it is critical to keep in mind potential threats to validity. These threats to validity are considered potential threats because not all of them will apply to every DSS developed using the SEPOMF. It is important to discuss threats to validity because doing so helps clarify the risks of applying a SEPOMF DSS and reduces the likelihood that a decision maker will make an ill-advised decision using a SEPOMF DSS. Two types of validity are considered: internal and external validity. Findings from a study have internal validity if effects observed in the dependent variable are actually caused by the independent variable and not by other factors[21]. External validity refers to whether the causal relationships from the study can be generalized beyond the study conditions[21]. It is necessary to consider both types of validity when applying the SEPOMF.

Table 1 provides an overview of these potential threats. Each row (after the title row) describes a particular potential threat to validity. The first column describes whether the potential threat is an internal or an external threat to validity. The second column describes the potential threat to validity, and the third column describes possible mitigations to each potential threat to validity. These mitigations may not in all cases remove or totally eliminate the threat to validity.

Table 1. Potential threats to validity when the SEPOMF is applied.

Category	Potential Threat	Mitigations
Internal	Relationships in objective function are not causal.	Gather large samples of data and explore competing theories.
	Optimization process converges to a suboptimal local maxima.	Use global optimization to improve the likelihood that global optimal is found.
External	Optimization model causes objective function to extrapolate (be evaluated outside the domain of the historical data used to develop objective function).	Analyze diagnostic statistics to identify instances of extrapolation (which may be hidden), and consider other approaches if extrapolation cannot be avoided.
	There are systematic differences between proposals used to develop the model and the proposal being optimized.	Examine the context of each historical proposal effort and carefully evaluate the applicability of each historical proposal effort.

5. Validity of the Framework

Before applying any model, it is first necessary to assess its validity. The SEPOMF is not exactly a model, but it is a framework that can be used to develop and solve optimization models. Nonetheless, there is value in validating the SEPOMF. If an analyst uses an invalid framework to develop and solve optimization problems, there is limited hope of finding valid optimal solutions. Validating a modeling framework, however, is by no means sufficient to guarantee a valid result will ultimately be found. It is still possible to use the framework to develop invalid models and get bad recommendations from the DSS. In an ideal situation, one would develop a model based on a subset of data and use another subset of sequestered data (data not used to develop the regression model) to verify that the

predicted model outputs match the response values in the sequestered data set. However, a sufficient quantity of data was not available to do this, and hence this is left for future work.

The SEPOMF example DSS concept with an objective function of maximizing the probability of contract award was evaluated using two methods. In the first method, the framework was presented to a number of different individuals with varied professional backgrounds, and these individuals provided feedback. These include individuals from academia with expertise in optimization, regression analysis, and systems engineering. In addition, a number of other experts with industry experience in using systems engineering on proposals reviewed the framework and provided feedback. The framework presented in this paper was refined per inputs received through this validation process.

The second method involved applying a structured process with a formal presentation and a set of carefully crafted questions to ask validators. No literature was found to guide a structured process of validating an optimization modeling framework. In the absence of such guidance, the model tests defined by Richardson and Pugh[22], originally conceived for system dynamics models, were analyzed for applicability to a modeling framework[4]. These model tests can be used to potentially improve a model by better aligning it with reality[22]. These model tests examine a number of dimensions of a valid model. These dimensions address both the structure and behavior of a model. The tests cover consistency between the model and the system or process being modeled, the suitability of the model to answer the questions it is being used to answer, and the model's ability to provide true insight that would otherwise not be available to the decision maker. From this set of model tests, a handful of questions were derived that apply to optimization modeling frameworks. These questions serve as the basis for validation.

Table 2 displays the questions that were asked of validators related to the SEPOMF and how each of those questions map to model tests from Richardson and Pugh[22]. The first column in Table 2 is the general activity type, the second describes a model test, including whether the test addresses the model's structure or behavior, and the third column presents the derived, SEPOMF-specific questions. For some of the Richardson and Pugh model tests, there were no analogous questions asked. This was the case for the following structure-related model test: dimensional consistency and extreme condition tests in equations. There were no questions asked related to any of the behavior aspects of the SEPOMF.

Four professionals were asked to validate the modeling framework. In order for a validator's inputs to be considered, the validator had to meet certain criteria. Each validator had to:

- Have participated in at least five proposal efforts from the supplier perspective where complex systems were being engineered,
- Have used systems engineering on proposals for complex systems,
- Have expertise in systems engineering processes,
- Have an understanding of optimization modeling, and
- Have an understanding of regression models.

All four individuals affirmed their qualifications.

Separate presentations were given to each of the four professionals. The presentations provided an overview of the SEPOMF, including purpose, scope and example models, to ensure validators understood what they were validating. In each presentation there were opportunities for validators to ask questions as the material was being presented. Then, validators were asked to independently fill out a questionnaire verifying that their credentials satisfy the criteria to validate. Validators also answered the pertinent set of questions from Table 2. The validator responses relating to the SEPOMF were compared side by side, and resolutions to the validator comments were determined. As a result of the validator feedback, some details of how the framework was described were refined. Examples of the refinements include preconditions for using the framework being more clearly defined and more explanation given as to how the values of the constraints impact the recommended solution.

6. Conclusions and Future Work

This paper describes the SEPOMF, discusses how to use the SEPOMF and presents information related to an example DSS defined using the SEPOMF. Validation efforts for the SEPOMF are also described. For additional details related to the SEPOMF, refer to Smartt[4]. The SEPOMF provides organizations a way to optimize how they use systems engineering on proposals to maximize the probability of contract awards. Considering the important role

systems engineering plays on proposals for complex systems, optimizing how systems engineering is used on proposals has the potential to improve the chance of survival for an organization. However, the framework presented in this paper is just a beginning to optimizing the use of systems engineering on proposals. More work should be done in this important area. To begin with, a sufficient quantity of historical proposal effort data needs to be collected to actually develop a DSS using the SEPOMF. This will help further mature the SEPOMF concept. Other technical issues will likely become apparent once real data is collected and an actual DSS is developed using that data. In addition, applying the SEPOMF to actual project data may help attain user buy-in to the SEPOMF modeling concept and facilitate additional validation for models developed using the SEPOMF.

The future research on optimizing the use of systems engineering on proposals, however, should be even broader in scope. While focusing on using systems engineering on proposals to be awarded contracts is a necessary objective, it is by no means sufficient. Other objectives should be considered. A key other objective is to earn a profit from executing those contracts. It may be that when the profit objective is considered, different levels of investments in systems engineering labor are recommended. There could be a range of investment levels that are sufficient to capture contracts but insufficient to propose a solution that allows the contract to be executed profitably[3]. The framework may also be expanded to allow multiple objectives (that cannot be consolidated into a single function) to be considered and to allow time constraints (e.g., a deadline that must be met) as well as resource constraints. A more expansive model such considering multiple objectives and time has even more potential to guide decision makers in using systems engineering on proposals. Gaining a better understanding of the relationships between investments in systems engineering on a proposal and desired outcomes will help organizations profit and ultimately survive.

Table 2. Modeling framework validation questions derived from Richardson and Pugh model tests.

Activity Type	Test	Relevant Questions
Consistency	Structure – Boundary structural adequacy tests	1.) Are there important variables that are missing in the SEPOMF formulation that should be included? If so, please explain. 2.) Are there variables included in the SEPOMF formulation that are extraneous and should be removed? If so, please specify which variables and explain why you believe that they are extraneous.
Suitability	Structure – Face validity	1.) Do the equations and inequalities (e.g., the constraints) presented in the mathematical programming formulation of the optimization model appear to reasonably represent the variables and relationships related to the use of systems engineering on proposals? If not, please describe issues that you see. 2.) Do you believe that a reasonable fit exists between the variables and structure of the SEPOMF and the essential characteristics of the use of systems engineering on proposals?
	Structure – Parameter validity	Are the variables presented in the mathematical programming formulation of the optimization model recognizable in terms of the use of systems engineering on proposals? If not, please explain.
Model Utility and Effectiveness	Structure – Appropriateness of structure	Is the level of simplicity or complexity and level of aggregation or richness of detail in the SEPOMF appropriate to allow a decision maker to maximize the probability of contract award given a specific budget? If not, please explain.

References

1. Smartt C, Ferreira S. A systems engineering perspective on proposal management. *IEEE Systems Journal* 2012;**6(4)**:667-674.
2. Philbin SP. Bid management: a systems engineering approach. *The Journal of High Technology Research* 2008;**19(2)**:114-127.
3. Smartt C, Ferreira S. Advancing systems engineering in support of the bid and proposal process. *Journal of Systems Engineering* 2011;**14(3)**:255-266.
4. Smartt C. *Optimizing the use of systems engineering on proposals*. Doctoral Dissertation: University of Texas at Arlington; 2013.
5. Nemhauser GL, Rinooy Kan AHG. *Handbook in operations research and management science*. Amsterdam: Elsevier; 1998.
6. OptTek, *Defining decision variables*, Available at http://www.opttek.com/documentation/v62engine/OptQuest%20Engine%20Documentation/WebHelp/Defining_decision_variables.htm (Last accessed 10/11/2013).
7. Cagno E, Caron F, Perego A. Multi-criteria assessment of probability of winning in the competitive bidding process. *International Journal of Project Management* 2001;**19(6)**:313-324.
8. Chapman CB, Ward SC, Bennell JA. Incorporating uncertainty into competitive bidding. *International Journal of Project Management* 2000;**18(5)**:337-347.
9. Naert PA, Weverbergh M. Cost uncertainty in competitive bidding models. *Journal of the Operational Research Society* 1978;**29(4)**:361-372.

10. McAfee RP, McMillan J. Auctions and bidding. *Journal of Economic Literature* 1987;**25(2)**:699-738.10.
11. Merriam-Webster online, Available at www.merriam-webster.com (Last accessed 10/11/2013).
12. Power DJ. *Decision support systems: concepts and resources for managers*. Westport, CT: Quorum Books; 2002.
13. Keen PGW, Scott Morton MS. *Decision support systems: an organizational perspective*. Reading, MA: Addison-Wesley; 1978.
14. Cockburn A. *Writing effective use cases*. Boston: Addison Wesley; 2001.
15. Agresti, A. An introduction to categorical data analysis. New York: John Wiley and Sons; 1996.
16. Lowe DJ, Pravar J. A logistic regression approach to modelling the contractor's decision to bid. *Construction Management and Economics* 2004;**22(6)**: 643-653.
17. Kutner, MH, Nachtsheim, CJ, Neter J, Li W. *Applied linear statistical models*. Boston: McGraw-Hill; 2005.
18. Montgomery DC, Peck EA, Vining GC. *Introduction to linear regression analysis* 5th ed. Hoboken, NJ: John Wiley and Sons; 2012.
19. Harrell FE, Lee KL, Matchar DB, Reichert TA. Regression models for prognostic prediction: advantages, problems, and suggested solutions. *Cancer Treatment Reports* 1985;**69(10)**:1071-1077.
20. Peduzzi P, Concata J, Kemper E, Holford TR, Feinstein AR. A simulation of the number of events per variable in logistic regression analysis. *Journal of Clinical Epidemiology* 1996;**49(12)**:1373-1379.
21. Rubin A, Babbie ER. *Research methods for social work*. Beverly, MA: Wadsworth; 2007.
22. Richardson GP, Pugh III A. *Introduction to system dynamics modelling*. Cambridge MA: The MIT Press; 1981.